A generalization of the PAC learning in product probability spaces (Model theoretic aspects of the notion of independence and dimension)

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A generalization of the PAC learning in product probability spaces

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Abstract

Three notions dependent theory, VC-dimension, and PAC-learnability have been found to be closely related. In addition to the known relation among these notions in model theory, finite combinatorics and probability theory, Chernikov, Palacin, and Takeuchi found a relation between n-dependence and VC_n-dimension, which are generalizations of dependence and VC-dimension respectively. We are now working to find a generalization of PAC-learnability corresponding to the above two generalizations. This attempt is a joint work with Takayuki Kuriyama and Kota Takeuchi. In this article, we see basic definitions and known results as well as some examples.

1 Introduction

It is known that dependent theory, or NIP theory, has close relation to the notions from finite combinatorics and probability theory, VC-dimension and PAC-learnability, respectively. In [1], [2], Shelah introduced a generalized notion of dependence, n-dependence. Recent study [7] of Chernikov, Palacin, and Takeuchi characterized n-dependence by VC_n-dimension, which is a generalization of VC-dimension. However, the corresponding generalization of PAC-learnability is remained to be unknown.

We attempt to find the generalization of PAC-learnability corresponding to the generalization from dependence to n-dependence and from VC-dimension to VC_n-dimension. The attempt is a joint work with Takayuki Kuriyama and Kota Takeuchi. Our main results are specifically presented in another article of ours in this Kôkyûroku.

In this article, we first recall the definitions of VC-dimension and PAC-learnability and the equivalence between these notions in section 2. Also, we mention Sauer-Shelah lemma there. In section 3, we see the definition of VC_n-dimension and the corresponding generalization of Sauer-Shelah lemma. After that, we introduce PAC_n-learnability and examine an example in section 4.

2 Preliminaries

We first recall the elementary notions in VC-theory. VC-dimension was introduced by Vapnik and Chervonenkis in [4], but in a different symbol.

Definition 2.1 (Vapnik, Chervonenkis [4]). Let X be a set and $\mathcal{C}$ be a subclass of the power set of X. We identify a subset C of X with the indicator function of C. This is because we need to clarify the domain of C in case we restrict the universal set X to some subset.

1. For a subset A of X, we write $\mathcal{C}|_A$ for the set $\{ C|_A \mid C \in \mathcal{C} \}$.
2. A subset A of X is said to be shattered by $\mathcal{C}$ if $\mathcal{C}|_A = 2^A$.
3. We define the VC-dimension of $\mathcal{C}$ by

$$\mathrm{VC}(\mathcal{C}) = \sup \{ |A| \mid A \text{ is a finite subset of } X \text{ shattered by } \mathcal{C} \}.$$

Definition 2.2 (Shatter function). For a class $\mathcal{C}$ of subsets of X, we define $\pi_{\mathcal{C}} : \omega \to \omega$ the shatter function of $\mathcal{C}$ as follows:

$$\pi_{\mathcal{C}}(m) = \sup \{ |\mathcal{C} \cap A| \mid A \text{ is an } m\text{-element subset of } X \},$$

where $\mathcal{C} \cap A = \{ C \cap A \mid C \in \mathcal{C} \}$.

The following lemma is known as Sauer-Shelah lemma. In this article, we just state the asymptotic behavior of shatter functions. For a more specific estimate, see [7].

Lemma 2.3. *Suppose* $\mathrm{VC}(\mathcal{C}) = d$. *Then,* $\log(\pi_{\mathcal{C}}(m)) = O(\log m)$.

Valiant introduced the notion of PAC-learnable in [3]. Here, for simplicity in measurability arguments, we restrict the universal set X to $\mathbb{R}^k$ or a product space of intervals in $\mathbb{R}$.

Definition 2.4 (Valiant [3]). Let X be $\mathbb{R}^k$ or a product space of intervals in $\mathbb{R}$, $\mathfrak{B}$ be the Borel set of X and $\mathcal{C}$ be a subset of $\mathfrak{B}$.

1. $\mathcal{C}_{\mathrm{fin}} = \{ C|_A \mid C \in \mathcal{C}, \text{ and } A \text{ is a finite subset of } X \}$.
2. $D(\bar{a}) = \{ a_0, \ldots, a_{m-1} \}$ for a tuple $\bar{a} = (a_0, \ldots, a_{m-1})$.
3. Let $H : \mathcal{C}_{\mathrm{fin}} \to \mathfrak{B}$ be a function. $\mathcal{C}$ is said to be PAC-learnable with learning function H if for all $\varepsilon, \delta > 0$, there exists $N \in \omega$ such that for an arbitrary measure $(\mu, \mathfrak{B})$ on X, an arbitrary $C \in \mathcal{C}$, and $m \geq N$,

$$\mu^m(\{ \bar{a} \in X^m \mid \mu(H(C|_{D(\bar{a})}) \triangle C) > \varepsilon \}) \leq \delta.$$

Here, μ^m is the product measure and $\triangle$ is the symmetric difference of two sets.

For a concept class $\mathcal{C}$, the finiteness of $\mathrm{VC}(\mathcal{C})$ and the PAC-learnability of $\mathcal{C}$ are equivalent under some condition. This theorem was essentially proved in [4], but in a different notation from here.

Theorem 2.5 (Vapnik, Chervonenkis [4]). *Let X be $\mathbb{R}^k$ or a product space of intervals in $\mathbb{R}$, $\mathfrak{B}$ be the Borel set of X and $\mathcal{C}$ be a well-behaved subclass of $\mathfrak{B}$. The following are equivalent:*

1. *$\mathcal{C}$ has finite* VC*-dimension.*

2. *$\mathcal{C}$ is* PAC*-learnable.*

We do not look closely into the property of being well-behaved, which is related to measurability. For details, see [5, Appendix A].

3 VC_n-dimension

In this section, we see a generalization of VC-dimension.

Definition 3.6 ([7]). Let $X_0, \dots, X_{n-1}$ be infinite sets, X be the direct product $\prod_{i<n} X_i$, and $\mathcal{C}$ be a subclass of the power set of X.

1. A subset A of X is said to be a box of size m if $A = \prod_{i<n} A_i$ for some subsets A_i of X_i with $|A_i| = m$, $i < n$.

2. We define the VC_n-dimension of $\mathcal{C}$ by
$$\mathrm{VC}_n(\mathcal{C}) = \sup \{\, m \mid A \text{ is a box of size } m \text{ that is shattered by } \mathcal{C} \,\}.$$

Example 3.7. Let $X = [0,1] \times [0,1]$, $\mathcal{C}_1$ be "the set of all finite union of subintervals in $[0,1]$," and $\mathcal{C} = \{\, C_1 \times C_2 \mid C_1, C_2 \in \mathcal{C}_1 \,\}$. Then, $\mathrm{VC}(\mathcal{C}) = \infty$ and $\mathrm{VC}_2(\mathcal{C}) = 1$.

Indeed, n-element set $\{\, (i/n, i/n) \mid i < n \,\}$ is shattered by $\mathcal{C}$. Hence $\mathrm{VC}(\mathcal{C}) = \infty$ holds. For any box $B = \{\, (a_i, b_j) \mid 1 \le i, j \le 2 \,\}$ of size 2, there do not exist C in $\mathcal{C}$ that satisfies $B \cap C = B \setminus \{\, (a_2, b_2) \,\}$. This is the case because for any C in $\mathcal{C}$, $C = C_1 \times C_2$ for some C_1 and C_2 in $\mathcal{C}$ by definition and so $\{\, (a_1, b_1), (a_2, b_2) \,\} \subset C$ implies $B \subset C$. □

Definition 3.8 (Shatter function corresponding to VC_n-dimension). Let $X_0, \dots, X_{n-1}$ be infinite sets, X be the direct product $\prod_{i<n} X_i$, and $\mathcal{C}$ be a subclass of the power set of X. We define $\pi_{\mathcal{C},n} : \omega \to \omega$ the shatter function corresponding to VC_n-dimension of $\mathcal{C}$ as follows:
$$\pi_{\mathcal{C},n}(m) = \sup \{\, |\mathcal{C} \cap A| \mid A \text{ is a box of size } m \text{ of } X \,\},$$
where $\mathcal{C} \cap A = \{\, C \cap A \mid C \in \mathcal{C} \,\}$.

It is known that a generalization of Sauer-Shelah lemma holds for VC_n-dimension. Here, we focus on the asymptotic behavior as above. For a more specific estimate, see [7].

Lemma 3.9 ([7]). *Suppose $\mathrm{VC}_n(\mathcal{C}) = d$. Then, $\log(\pi_{\mathcal{C},n}(m)) = O(m^{n-\varepsilon} \log m)$, where $\varepsilon = d^{-(n-1)}$.*

4 PAC$_n$-learnability

We introduce a new notion. We are currently working to figure out if this generalization of PAC-learnability corresponds to that of VC-dimension stated in section 3. As above, for simplicity in measurability arguments, we continue to restrict the universal set X to $\mathbb{R}^k$ or a product space of intervals in $\mathbb{R}$.

Definition 4.10. Let $X_0, \ldots, X_{n-1}$ be Euclidian spaces or intervals, X be the product space $\prod_{i<n} X_i$. Also, let $\mathfrak{B}_i$ and $\mathfrak{B}$ be the Borel sets of X_i and X respectively, and $\mathcal{C} \subset \mathfrak{B}$.

1. For $a = (b_0, \ldots, b_{n-1})$ in X, we put

$$D_n(a) = \bigcup_{i<n} X_0 \times \cdots \times X_{i-1} \times \{ b_i \} \times X_{i+1} \times \cdots \times X_{n-1}.$$

2. $D_n(\bar{a}) = \bigcup_{i<m} D_n(a_i)$ for a tuple $\bar{a} = (a_0, \ldots, a_{m-1})$ in X^m.

3. $\mathcal{C}_{\text{fin}}{}^n = \{ C|_{D_n(\bar{a})} \mid C \in \mathcal{C},\ \bar{a} \in X^m, \text{ and } m \in \omega \}$.

4. Let $H : \mathcal{C}_{\text{fin}}{}^n \to \mathfrak{B}$ be a function. $\mathcal{C}$ is said to be PAC$_n$-learnable with learning function H if for all $\varepsilon, \delta > 0$, there exists $N \in \omega$ such that for arbitrary measures $(\mu_i, \mathfrak{B}_i)$ on X_i, an arbitrary $C \in \mathcal{C}$, and $m \geq N$,

$$\mu^m(\{ \bar{a} \in X^m \mid \mu(H(C|_{D_n(\bar{a})}) \triangle C) > \varepsilon \}) \leq \delta.$$

Here, μ is the product measure $\prod_{i<n} \mu_i$ and $\triangle$ is the symmetric difference of two sets.

Example 4.11. Let $X = [0,1] \times [0,1]$, and $\mathfrak{B}$ be the Borel set of $[0,1]$. Also, we put $\mathcal{C}_1 =$ "the set of all finite union of subintervals in $[0,1]$," and $\mathcal{C} = \{ C_1 \times C_2 \mid C_1, C_2 \in \mathcal{C}_1 \}$. Then, $\mathcal{C}$ is PAC$_2$-learnable.

For a finite subset $\bar{a}$ of X, we define a learning function $H : \mathcal{C}_{\text{fin}}{}^2 \to \mathfrak{B}$ by

$$H(C|_{D_2(\bar{a})}) = p_1(C|_{D_2(\bar{a})}) \times p_2(C|_{D_2(\bar{a})}).$$

Here, p_1 and p_2 are the projection maps. Observe that we have $H(C|_{D_2(\bar{a})}) = C$ if there are a_1 and a_2 in $\bar{a}$ such that $p_1(a_1) \in p_1(C)$ and $p_2(a_2) \in p_2(C)$.

In order to show that $\mathcal{C}$ is PAC$_2$-learnable with learning function H, we take arbitrary $\varepsilon, \delta > 0$ and for sufficiently large m with respect to ε and δ, arbitrary measures $(\mu_i, \mathfrak{B}_i)$, and C in $\mathcal{C}$, we estimate $\mu^m(\{ \bar{a} \in X^m \mid \mu(H(C|_{D_2(\bar{a})}) \triangle C) > \varepsilon \})$, where $\mu = \mu_1 \times \mu_2$. Because $H(C|_{D_2(\bar{a})}) \subset C$ holds, if $\mu(C) \leq \varepsilon$ then $\mu^m(\{ \bar{a} \in X^m \mid \mu(H(C|_{D_2(\bar{a})}) \triangle C) > \varepsilon \}) = 0$. We assume $\mu(C) > \varepsilon$. By the above observation, we have

$$\begin{aligned}
&\mu^m(\{ \bar{a} \in X^m \mid \mu(H(C|_{D_2(\bar{a})}) \triangle C) > \varepsilon \}) \\
\leq &\mu^m(\{ \bar{a} \in X^m \mid p_1(\bar{a}) \cap p_1(C) = \emptyset \text{ or } p_2(\bar{a}) \cap p_2(C) = \emptyset \}) \\
\leq &\mu^m(\{ \bar{a} \in X^m \mid p_1(\bar{a}) \cap p_1(C) = \emptyset \}) + \mu^m(\{ \bar{a} \in X^m \mid p_2(\bar{a}) \cap p_2(C) = \emptyset \}) \\
\leq &2(1-\varepsilon)^m \leq \delta.
\end{aligned}$$

The last inequality above is derived from the way we chose m. □

We have reached a result of one side of the equivalence between finiteness of the VC_n-dimension and the PAC_n-learnability. This result was obtained by joint work with Kuriyama and Takeuchi. For the proof, refer to another article of ours in this Kôkyûroku.

Theorem 4.12. *Every* PAC_n*-learnable class has finite* VC_n*-dimension.*

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